BRINGING COMMUNITY OWNED WIND

POWER TO OKLAHOMA USING

SCHOOL DISTRICTS

By

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Abstract:

From the demand for wind-produced energy, wind farms have been installed across the nation. The majority of large-scale wind farms are corporate owned. Community owned wind farms differ in that they are a locally owned asset. With the large number of people within the community involved, reaching agreements and working together while also maintaining project support can slow or end implementation plans.

The complexity of community owned wind power production could be overcome by targeting school districts for implementation. Schools are a logical starting place for development because they offer a variety of people and skill sets, and pre-existing collaboration within the school and community. Schools provide the unity needed for success. Support for community owned wind power using school districts would increase if Oklahomans could be shown what drives the success of these communities already taking advantage of school based wind power production. Therefore, the purpose of this study is to establish the probability for the success of implementation in Oklahoma by first finding the drivers behind successful production of current wind power installed in schools.

A variety of statistics and regression analyses were used to analytically produce a reliable list of significant drivers for successful implementation of wind power production.   Through a three-step statistical analysis, a final multivariate regression model was chosen resulting in the final regression equation. By this equation, it is known that the only potential variable that has any effect on the dependent variable is the grant assistance received by each school site. Community wind projects need funding, but by using school districts as location sites the payback period is not as strong of a focus. School’s do not necessarily have to first show profitability of the project, only that they can afford the upfront costs and then over time (a longer period than needed in a commercial wind project) make a profit.

The cluster analysis results showed one group of school sites spatial encompassing Oklahoma. By focusing on the high level similarities seen in this cluster, the beginnings of what Oklahoma should focus on for implementation is already given.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

"Wind has been the fastest growing source of electricity generation in the world through the 1990s" (National Renewable Energy Laboratory, 2009). With such a huge increase in demand for wind-produced energy, a vast amount of wind farms have popped up all across the nation, including over 11 corporate owned wind farms currently located in Oklahoma (Oklahoma Wind Power Initiative, 2010). Wind farms are comprised of several wind turbines, in varying sizes, construction, and ownership. This study is focused on the ownership aspect of wind power production, specifically concentrated on bringing community owned wind farms to Oklahoma.

The majority of large-scale wind farms, especially those already in production in Oklahoma, are corporate owned. Community owned wind farms are different in that they are a locally owned asset. "Locally-owned means that one or more members of the local community has a significant direct financial stake in the project... The term Community Wind refers to the method and intention of development rather than the size of the project" (Windustry, 2011). From first glance, community wind power may appear to be purely a smaller version of corporate wind power production; however, community owned wind power production could by definition use any scale turbine for any scale project, as long as the local community holds ownership. Typically, community landowners have smaller land area to implement a wind project and smaller wind power production needs, which leads to a need for a smaller turbine that might be utilized in commercial scale projects. Even though an average community based wind power project is on a smaller scale of development, it offers advantages and benefits over larger scale corporate productions in three keys areas: economic, social, and environmental.

Community owned wind power "substantially increase[es] the economic benefits for the community over projects owned by out-of-area corporate developers " (Pahl, 2008). Own Energy, a prominent community wind developer, insists community based wind power offers two significant additional incentives for the local economy. The first of these incentives is that since the ownership of wind farm is within the community "profits are recycled there" creating jobs and wages as well as additional income to existing businesses. The second advantage is unlike corporate owned wind farms "community wind developers and their financial partner are typically U.S.-based" thus assuring that all benefits stay within the U.S. economy (Borst, 2012). In "Community vs. Corporate Wind: Does it Matter Who Develops the Wind in Big Stone County, MN?" (2006), Kildegaard and Myers-Kuykindall come to similar conclusions that community owned wind power production allows significantly more income to remain in the county than corporate owned wind power production. Income could result directly from selling electricity back to the electrical company or from savings from a decreased utility bill. Income could also result indirectly in the form of new jobs and businesses within the community. This indirect form of income can be seen in an increased need for individuals who are able to troubleshoot turbine problems, such as electrical trouble after a storm, or increased demand for local cement for turbine pads.

Both direct and indirect sources of income create energy independence and connect people to their power source, which increases personal environmental responsibility (Windustry, 2011). Community based wind projects have the environmental benefit over corporate owned wind projects in that the small scale wind turbines take up less space and allow for more space or farm land to be used for its original purpose while simultaneously producing clean energy (Borst, 2007). According to a recent study sponsored by the National Renewable Energy Laboratory titled “Land-Use Requirements of Modern Wind Power Plants in the United States”, commercial scale wind turbine, depending on the placement pattern, typically require a quarter of an acre of land footprint (Denhol et al. 2009). This means that each turbine requires almost 11,000 square feet of land for installation. As previously discussed, community wind power projects are not defined by scale and can in fact use the same scale turbines as commercial wind power, although characteristically community based wind power does utilize a smaller turbine. The average area needed for a small scale turbine, like the ones typically recommended by the U.S. Department of Energy community based wind power, require 25 square feet of land (U.S. Department of Energy 2010). It should be noted that smaller scale turbines have proportionately less power generation capacity and produce at greater costs per kilowatt hour than large turbines.

Lastly, there are also social benefits of community wind, such as promoting energy independence and local production control. The majority of electricity consumed is generated from fossil fuels, such as coal and natural gas, which are often mined from within the United States. However, on a community scale, “millions of consumers essentially import energy into their area” since the electricity is not generated in their community (Stockwell 2009). Energy independence and local production control strengthens the community socially by allowing local residents to make decisions for themselves and their community. This increases awareness and concern for the well being of the whole community.

If community wind power production has such overwhelming benefits, why are the majority of wind farms corporate owned? The simple answer is community owned wind power requires the support and unity of an entire community and many different skills of several people working simultaneously in order for success. Often the collective group within a community has several different skills obtained from different lifestyles and careers, but the skills directly related to wind power development may be lacking. However, coordination and opportunities for involvement can make up for shortcomings in knowledge and direct experience (Stockwell 2009). Even with community support, the largest barriers to community wind development are financing, ownership structure, scale, and siting constraints (Kildegaard & Myers-Kuykindall, 2006). Community based wind farms differ from large-scale wind farms in that determining the ownership structure is very difficult. Unlike large-scale wind farms that are owned by one corporation, the funding sources of small-scale wind farms are numerous, which can create a complex network of ownership partners within the community. This intrinsic ownership means a large group of independent people is responsible for decision making increasing difficulty of arriving at final decisions. Final decisions on scale and siting are the last hurdles that small-scale wind power development must overcome. Scale and siting constraints must often be considered concurrently, since the scale of the project affects many siting decisions. Siting constraints include access to transmission lines, power purchase agreements, zoning restrictions, protected lands, etc. With such a large number of people involved, reaching agreements and working together while also maintaining the support of the community can slow or even end implementation plans for community wind.

The complexity of community owned wind power production could be overcome by targeting school districts for implementation. Schools are a logical starting place for development in that they offer a variety of people and skill sets, as well as strong, pre-existing collaboration within the school and within the community. Schools provide the unity needed for success. However, school districts still require outside support for implementation in the form of funding sources and best fit implementation plans. The United States Department of Energy's Wind Powering America Initiative has developed the Wind for Schools Project in order to provide this needed outside support by providing comprehensive implementation plans, establishing in state Wind Application Centers, and implementing wind-related curriculum into the classroom. The program's primary goal is to "raise awareness in rural America about the benefits of wind energy while simultaneously developing a wind energy knowledge base in future leaders of our communities, states, and nation." (National Renewable Energy Laboratory, 2007). The program began in 2005 and as of January 1, 2012 had 118 sites in 26 states including Alaska, Colorado, Georgia, Idaho, Illinois, Iowa, Kansas, Maine, Maryland, Massachusetts, Michigan, Minnesota, Montana, North Carolina, Nebraska, Nevada, New York, Ohio, Oregon, Pennsylvania, Rhode Island, South Dakota, Texas, Utah, Vermont, and Virginia (U.S. Department of Energy, 2010). While participation in the program is not a necessity for success, it spurs area interest in community based wind development.

Oklahoma is currently ranked 9th in the Unites States for wind power resource and 4th in the nation for cumulative installed wind capacity (American Wind Energy Association, 2013). However, Oklahoma is not currently involved in the Wind for Schools Project, nor is it taking advantage of benefits schools offer for implementation locations of community based wind power production. The states with schools involved in the project also have high wind energy potential. Texas, Kansas, South Dakota, Montana, Nebraska, Minnesota, and Iowa are all in the top 10 Wind Energy Potential states in the nation. However, there seems to be more to the decision making process than just available wind energy. For example, Virginia, Rhode Island, and North Carolina are not even in the top 30 Wind Energy Potential states in the nation (AWEA Wind Energy Projects, 2007). The success of those states involved is dependent on the support within the community for community owned production.

Possibly, non-utility-scale wind has been absent in Oklahoma not because of a lack of knowledge, but due to a lack of plausibility proof. As other states have learned, “increased success rate[s] of community wind projects leads to increased knowledge, awareness, and acceptance of wind power, thus reducing public opposition” (Borst, 2012). Support for community owned wind power using school districts in Oklahoma might increase if Oklahoma could be shown what drives the success of these communities already taking advantage of school based wind power production. Therefore, the purpose of this study is to establish the probability for the success of implementation in Oklahoma by first finding the drivers behind successful production of current wind power installed in schools.

In order to find the drivers behind a successful school based wind power project, the first step was to produce a list of hypothesized drivers. Then, the study used a variety of statistics and regression analyses to analytically produce a list of significant drivers for successful implementation of wind power production. Finally, the results of the analytical analyses of current school based wind power production were applied to Oklahoma, specifically in determining how Oklahomans can take advantage of the background knowledge to further community based wind power production utilizing schools.

CHAPTER II

METHODOLOGY

As discussed above, the purpose of this study was to discover the drivers behind successful installation and usage of the current school owned wind power production sites within the Wind Powering America Wind Energy for Schools project. To accomplish this, the methodology was broken into three main sections: General Analysis of the Variables, Correlation Analysis, and Regression Analysis. In the first section I used the literature collected in the previous chapter to create a list of predicted variables attributing to the success of the current operating sites within the Wind Powering America Wind Energy for Schools project. A general analysis of each of the variables was then performed in order to make certain of the robustness and completeness of the dataset. The last two sections encompass the analytical framework for establishing which variables in section one are the prominent drivers for success.

SECTION 1. GENERAL ANALYSIS OF THE VARIABLES

Section 1.1 describes each of the chosen variables, why each was chosen, and from where each dataset was obtained. The dependent variable or that variable which was determined by the other independent variables must measure the success of each of the existing school sites' wind projects. Section 1.2 details the general analysis preformed on each of the variables. This was a two-step process accomplished through a descriptive statistics analysis and two graphical analyses using a histogram and a probability plot.

SECTION 1.1 Variable Selection

Wind Power Generation Capacity

The amount of electricity generated was the "most important factor in determining the economic effectiveness of s small wind turbine" (Geiger et al. 2010). While the wind energy produced by each school site would have been an excellent measure of success, the Wind Powering America Wind Energy for School project was only recently widely implemented and many schools participating in the program had not yet reported production data to the program. With this consideration, a seemingly reasonable measure of success that was obtainable was the wind power generation capacity size of the wind turbines in operation at each site. Schools were encouraged by the program to use a SkyStream 3.7, 2.4 kilowatt wind turbine (National Renewable Energy Laboratory, 2007), however, the capacity size measured the entire projects capacity and was dependent on the number of turbines implemented by the school and if the school was able to implement a different turbine then the one recommended by the program.

The wind power generation capacity size was obtained from the Wind Powering America Wind Energy for Schools website for 2011 for 100 school sites. Only schools reporting the total wind power generation capacity for the entire project were included in the data set shown in Table 1 below. The data for each site's capacity was expressed in kilowatts (kW). Each site's latitude and longitude was used to create a shapefile in ESRI ArcMap 10 geographical information system (GIS) technology (ESRI, 2011). A shapefile was essentially a layer within a digital map that expressed geographical location as well as specific textual data corresponding to each entity within the layer.

Project Name	City	County	State
Williams Elementary-Middle School	Williams	Coconino	AZ
Walsh High School	Walsh	Baca	CO
Burlington High School	Burlington	Kit Carson	CO
Stratton High School	Stratton	Kit Carson	CO
Wray School District	Wray	Yuma	CO
Ponderosa High School	Parker	Douglas	CO
John Mall High School	Walsenburg	Huerfano	CO
Wellington Middle School	Wellington	Larimer	CO
Clay Central-Everly Community School District	Royal	Clay	IA
Eldora-New Providence High School	Eldora	Hardin	IA
Akron-Westfield Community School District	Akron	Plymouth	IA
Nevada High School	Nevada	Story	IA
Forest City Community School District	Forest City	Winnebago	IA
Northwood-Kensett Community School District	Northwood	Worth	IA
Clarion-Goldfield Community School District	Clarion	Wright	IA
Waukee High School	Waukee	Dallas	IA
Spirit Lake Community School District	Spirit Lake	Dickinson	IA
Midway Middle School	Rigby	Jefferson	ID
Rigby High School	Rigby	Jefferson	ID
Eagle Rock Jr. High	Idaho Falls	Bonneville	ID
Skyline High School	Idaho Falls	Bonneville	ID
Pocatello Community Charter School	Pocatello	Bannock	ID
Shelley High School	Shelley	Bingham	ID
Richard McKenna Charter High School	Mountain Home	Elmore	ID
Jerome Middle School	Jerome	Jerome	ID
Bureau Valley School District	Manlius	Bureau	IL
Rhodes School	River Grove	Cook	IL
Union City Community High School	Union City	Randolph	IN
Concordia Jr.-Sr. High School	Concordia	Cloud	KS
Quinter Unified School District	Quinter	Gove	KS
K-12 Kiowa County School	Greensburg	Kiowa	KS
Fairfield High School	Langdon	Reno	KS
Pretty Prairie Middle-High School	Pretty Prairie	Reno	KS
Blue Valley High School	Randolph	Riley	KS
El Saline Middle-High School	Brookville	Saline	KS
Moscow Junior/Senior High School	Moscow	Stevens	KS
Sterling Middle-High School	Sterling	Rice	KS
Smoky Valley High School	Lindsborg	McPherson	KS
Solomon High School	Solomon	Dickinson	KS
West High School	Wichita	Sedgwick	KS
Cape Cod Regional Technical High School	Harwich	Barnstable	MA
Centerville Elementary School	Centerville	Barnstable	MA
Upper Cape Cod Regional Technical School	Bourne	Barnstable	MA
Beverly High School	Beverly	Essex	MA
Carlton Elementary School	Salem	Essex	MA
McGlynn Elementary and Middle School	Medford	Middlesex	MA
North Quincy Street Elementary School	Brockton	Plymouth	MA
Stephen E. Decatur Middle School	Berlin	Worcester	MD
Laker Elementary School	Pigeon	Huron	MI
Onsted High School	Onsted	Lenawee	MI

Project Name	City	County	State
Zeeland West high School	Zeeland	Ottawa	MI
Lac Qui Parle Valley High School	Madison	Lac Qui Parle	MN
Mahtomedi High School	Mahtomedi	Washington	MN
Pipestone Area School District	Pipestone	Pipestone	MN
Fergus High School	Lewistown	Fergus	MT
Valier High Schol	Valier	Pondera	MT
Wolf Point High School	Wolf Point	Roosevelt	MT
Broadwater High School	Townsend	Broadwater	MT
Forsyth High/Middle School	Forsyth	Rosebud	MT
Glasgow High School	Glasgow	Valley	MT
Cascade Public Schools	Cascade	Cascade	MT
Fairfield Public Schools	Fairfield	Teton	MT
Park high School	Livingston	Park	MT
Stanford School	Stanford	Judith Basin	MT
Madison High School	Marshall	Madison	NC
Pleasanton Public Schools	Pleasanton	Buffalo	NE
Logan View Public Schools	Hooper	Dodge	NE
Diller-Odell Public Schools	Odell	Gage	NE
Hayes Center Public Schools	Hayes Center	Hayes	NE
Mullen Public Schools	Mullen	Hooker	NE
Creighton Public Schools	Creighton	Knox	NE
Norris Public Schools	Firth	Lancaster	NE
Cedar Rapids Public School	Cedar Rapids	Boone	NE
Elkhorn Valley Schools	Tilden	Madison	NE
Papillion-LaVista Public Schools	Papillion	Sarpy	NE
Crawford Public Schools	Crawford	Dawes	NE
Garden County Public Schools	Oshkosh	Garden	NE
Rosemary Clarke Middle School	Pahrump	Nye	NV
Shade-Central City School District	Cairnbrook	Somerset	PA
Portsmouth Abbey School	Portsmouth	Newport	RI
Elkton Public Schools	Elkton	Brookings	SD
Faith School District	Faith	Meade	SD
Sioux Falls Memorial Middle School	Sioux Falls	Minnehaha	SD
Douglas School District	Box Elder	Pennington	SD
Sanborn Central	Forestburg	Sanborn	SD
Selby High School	Selby	Walworth	SD
Yankton School District	Yankton	Yankton	SD
Dakota Valley School District	North Sioux City	Union	SD
Wessington Springs Elementary School	Wessington Springs	Jerauld	SD
Springlake-Earth Independent School District	Earth	Lamb	TX
Shallowater Independent School District	Shallowater	Lubbock	TX
South Weber Elementary School	South Weber	Davis	UT
Cyprus high School	Magna	Salt Lake	UT
Milford Elementary School	Milford	Beaver	UT
Milford High School	Milford	Beaver	UT
Three Peaks Elementary School	Cedar City	Iron	UT
Virginia Beach City Public Schools	Virginia Beach	Virginia Beach City	VA
Northumberland Middle and High School	Heathsville	Northumberland	VA
William Fleming High School	Roanoke	Roanoke City	VA
Wausau East High School	Wausau	Marathon	WI

Table 1. Existing 100 school sites in the Wind for Schools project reporting total wind capacity.

Wind Potential

Wind potential is the availability of wind energy theoretically at a location. The wind potential was derived from the annual average wind power measured at 50 meters high above the ground. This was then expressed in wind power classes 1 through 7, with 1 being unsuitable for development and 7 being superb (National Renewable Energy Laboratory , 2012). Table 2 depicts the details of these wind power classes, including class, resource potential, power density, and wind speed. I hypothesized this variable to be an important driver for the success of implementation of wind power production. Since high wind potential indicates more wind available to be converted into power, it was my prediction that the higher the wind class, the greater the project size implemented.

Wind potential classes were extracted from shapefile layers developed by the National Renewable Energy Laboratory for their Wind Powering America project. A shapefile layer was created for each state within in the United States using a MesoMap technology (Elliot & Schwartz, 2005) and historical weather data (National Renewable Energy Laboratory, 2012). Using ArcMap 10, information was pulled from the wind potential layer based on a layer created using the latitude and longitude of each of the 100 existing school sites in the Wind Power for Schools project.

Wind Power Class	**Resource Potential**	**Wind Power Density at 50m (W/m2)**	**Wind Speed at 50 m (m/s)**
Class 1	Unsuitable for Development	0-200	0-5.6
Class 2	Marginal	200-300	5.6-6.4
Class 3	Fair	300-400	6.4-7.0
Class 4	Good	400-500	7.0-7.5
Class 5	Excellent	500-600	7.5-8.0
Class 6	Outstanding	600-800	8.0-8.8
Class7	Superb	800-1600	8.8-11.1

Table 2. The 7 Wind Power Potential Classes ranked based on power density and wind speed.

Elevation

Elevation plays an important role in the capture of wind power in two main ways. At low elevations of about 3,000 feet above sea level or less, the wind power production potential will most likely to be increased with increasing altitude. Higher elevations up to 3,000 feet above sea level allow the turbine to be placed above obstacles that might create non-uniform wind patterns, such as sudden wind gusts from unlikely directions. However, at locations with elevations higher than about 3,000 feet above sea level the amount of wind power production potential decreases, because air density significantly decreases as elevation increases. Air density affects the amount of potential power the turbine can collect from the wind in that wind in lower density air cannot turn the turbine as effectively as air with a higher density. Recent studies have found the annual energy output estimates for small scale wind power production is about ten percent lower at 3,500 feet and about twenty percent lower at 7,000 feet than the same wind turbine at sea level (Geiger et al. 2010). The relatively denser air nearer seal level can lower the power production estimates enough to cause projects to be financially unfeasible.

This variable was often overlooked in wind placement analysis, especially in states with low elevations or uniform elevations over large land areas. However, this variable was potentially of interest and I hypothesized it to play a significant role in determining success in locations with more varying elevations.

The elevation data for each existing school site was obtained from the United States Geological Survey's National Elevation Dataset (NED). This USGS elevation dataset was prepared in 2009 in 10 to 30 meter resolution shapefiles for the states in the United States (U.S. Geological Survey, 2009). Using ESRI ArcMap 10 GIS technology information was pulled from the USGS NED layer based on a layer created using the latitude and longitude of each of the 100 existing school sites in the Wind Power for Schools project. The resulting output was the elevation in meters above sea level for each of the 100 school sites.

Land Cover/Surface Roughness

"Land cover" includes both the roughness of the land and the site availability or suitability. Land cover includes vegetation, water features, as well as any artificial features affecting the surface roughness. As surface roughness increases the wind speed in the first few hundred meters of the air will be slowed. Surface roughness is maximized in heavily wooded areas or areas with high levels of human development. Abrupt differences in land cover can also affect wind speed reaching the wind turbine (Ragheb, 2011). As discussed above, development can change the amount of wind the turbine receives. Also, land cover can indicate sites unavailable for construction due to ownership or protection.

For this study the focus of land use was on surface roughness. A 2006 National Land Cover Database (NLCD) GIS data file was obtained from the USGS (U.S. Geological Survey, 2011). The NLCD file gave each landcover type a numerical classification. This numerical classification was used as a reference for land cover type (Fry et al., 2011). I ordered the land cover designations in the data set according to the predicted surface roughness (Ragheb, 2011). The land cover type was compared to Ragheb's corresponding predicted surface roughness. Then values were assigned to each land cover type in order of increasing predicted surface roughness. After importing the data file into ArcMap 10, the NLCD's land cover type was extracted using a quarter-mile buffer around each of the school sites' latitude and longitude in the previously created shapefile. The dominant land cover type was extracted and referenced to the surface roughness designation previously created to give its estimated land cover roughness classification. Table 3 below shows the dominate land cover types found in the quarter mile buffer around each of the existing school sites, as well as the estimated surface roughness classification.

Surface Roughness Classification	Land Cover Classification	Land Cover Type
1	11	Water
27	81	Pasture/hay
48	71	Grasslands/herbaceous
56	82	Row crops
61	51	Shrubland
69	21	Low intensity residential
76	41	Deciduous forest
78	42	Evergreen forest
82	22	High intensity residential
87	23	Commercial/industrial/transportation

Table 3. Surface roughness classification for those land cover types found within a quarter-mile of the existing school sites.

Rural versus Urban

Rural versus urban effects include the differences in wind resource, interest of the residents, and space for installation. Rural locations often have a better wind resource and more space for implementation than urban areas. Rural areas often consist of farm or rangelands with plenty of open space ready for installation than urban areas. Interest of residents is more difficult to predict. On one hand, rural residents may have a high interest for the increased income and community benefits. On the other hand, urban resident might have a high interest in producing a clean electricity to offset current air pollution emissions or opposed to turbines as eyesores.

Overall, it was my prediction that rural settings produce a higher success rate for the completion and usage of wind power production. An Urban Areas 2010 TIGER/Line shapefile was downloaded from the U.S. Census Bureau Geography Division. The shapefile was imported into ArcMap10 along with a previous made shapefile of the existing school sites' location using the latitude and longitude. The information in the urban areas shapefile was extracted for each site's location and exported to indicate which of the current school sites were located in an urban area. The variable was denoted as 0 for a rural area or 1 for an urban area.

District Area Size

The district area size permits how much space is available for implementation. Often the turbine is required to be installed on or near schools grounds both for ease and lower cost of grid connection. Larger districts could result in a wide spread school owned area for installation. Therefore I predicted that the school districts with larger areas would have higher wind power generation capacity installment.

A School Districts 2010 TIGER/Line shapefile was downloaded from the U.S. Census Bureau Geography Division. The unified school district layer was chosen so that the entire district for both the elementary and secondary schools would be included, since this would be the total space available to the project. This shapefile was imported into AcrMap 10. Then the existing school site location shapefile was used to extract the data from the school districts layer. The data expressing the district size in square meters was exported.

School District Population

The district population effects school funding which is necessary for program implementation. Nationwide 37% of the annual school budget comes from local tax sources. Higher populations mean more incoming tax money that the school receives for budgeting (U.S. Department of Education, 2011). Areas with declining populations might not have the budget to cover installation costs due to a smaller population or less ability from the population to pay taxes. These areas might need to rely on outside funding in the form of donations or grants. Therefore it was my prediction that higher district populations will lead to higher wind power generation capacity.

Each school district's population was obtained from the U.S Census Bureau's Small Area Income and Poverty Estimates. The 2011 data were downloaded for the district by state into data tables. It was important to note that this data was based off estimates performed by the U.S. Census Bureau and may contain a estimation errors.

Number of Students per District

The number of students also affects the schools' funding. The larger the number of students attending the school, the more money the school receives from the state government budget (U.S. Department of Education, 2011). This incoming money might be able to cover implementation costs. Smaller schools, however, typically have a smaller total state support and less flexibility to possibly budget towards a project of this magnitude. The number of students per district was obtained from the Institute of Education Sciences' National Center for Education Statistics (Institute of Education Sciences, 2011). For consistency, the unified school district was used to calculate total student populations.

Per Capita Income

The per capita income (PCI) could affect possible outside funding opportunities. Schools already participating in wind power production have struggled with where to find money to cover completion costs. However, several schools have received outside donations from local residents to help overcome budget issues (Galluzzo & Osterberg, 2006). Schools relying on outside funding, such as donations, may have a better chance in receiving that funding if the average incomes of the surrounding citizens are higher. The 2010 American Community Survey 1 –year estimate PCI was obtained from the U.S Census Bureau for the total population for each of the counties the existing school sites were located. The PCI data was expressed in 2010 inflation-adjusted dollars (U.S. Census Bureau, 2010b).

Grants Received

Small-scale wind turbines, such as the 2.4kW wind turbine used in the Wind for Schools program cost about $6,000 each. Even though participation in the program lowers the cost to about $2,000 - $3,000 per turbine, this is still money the school is required to acquire alone (National Renewable Energy Laboratory, 2007). These upfront costs associated with installation create barriers for those areas or schools where funds are limited. An important determinant factor for funding is the availability of grants. The availability of state level grants varies with each state offering different amounts of money and different implementation criteria. There are also federal grants available through the U.S. Department of Energy (National Renewable Energy Laboratory, 2011).

The data on this variable was expressed as the dollar amount of grants used for installation of the project. This data was obtained through the assistance of several Wind Powering America Wind for Schools program employees (Baranowski, personal communication). Dollar amounts for each grant were figures rounded to the closest one hundred dollars. I was not able to locate grant endowment information for all 100 schools, since this information had not been reported to anyone with the Wind for Schools project. Therefore, the 10 schools without this information were eliminated from this study bringing the total number of existing school sites for this study to 90. Those schools removed from the study can be found in Table 4 on the following page.

Project Name	City	County	State
Williams Elementary-Middle School	Williams	Coconino	AZ
Smoky Valley High School	Lindsborg	McPherson	KS
Solomon High School	Solomon	Dickinson	KS
West High School	Wichita	Sedwick	KS
Cascade Public Schools	Cascade	Cascade	MT
Fairfield Public Schools	Fairfield	Teton	MT
Park high School	Livingston	Park	MT
Stanford School	Stanford	Judith Basin	MT
Rosemary Clarke Middle School	Pahrump	Nye	NV
Wessington Springs Elementary School	Wessington Springs	Jerauld	SD

Table 4. School sites which had not reported amount of grants received for the project.

Netting Price

Netting price is the amount the local electrical company is willing pay for produced electricity, which determines payback. Netting price is difficult to predict, first, because of widely varying electricity prices across the country. Second, not every state offers a net metering program. Currently 43 states offer net-metering programs in which the electric meters turn backwards as wind power is generated offsetting the electricity being used (The Green Power Network, 2011). The utility company buys any excess energy. States with net metering programs often buy back excess electricity generated by wind power at retail price. However, states without these programs allow the electricity provider to determine the price at which they buy back excess electricity.

In 2006 a summary report was released for 15 Iowa schools considering wind power production. Out of the 15 possible schools, four of the schools halted productions from going forward due to electricity companies offering buy back rates too low for excess energy (Galluzzo & Osterberg, 2006). Each of these schools emphasized the importance of establishing a contract with the electrical company for a buy back rate high enough for the school to be able to pay back high upfront costs of implementation. The schools also learned not to assume rates will be the same for all schools within the state or given area. This was shown through the varying buy back prices between the ten schools that implemented wind power production (Galluzzo & Osterberg, 2006). Although the effects of this variable were shown through these schools' examples, the netting price was a negotiated variable that will differ depending on any number of circumstances. This made it impossible to predict what the netting price was available to each project. Therefore, in order to include this variable in this study I would have needed data on each school's contract with the utility company. Since this information was not reported to the Wind for Schools project, it would have involved contacting each individual school to request said data. Due to these circumstances this variable was removed from the study.

SECTION 1.2 Descriptive Statistics

After the collection of the data for each variable, general descriptive statistics were ran on the data using a combination of the Data Analysis tool in the Microsoft Excel program(Microsoft Excel, 2013) and the General Descriptive tool in the SPSS software program Predictive Analytics SoftWare (PASW) (SPSS, Inc., 2009). The data analysis tool in Excel provided a general analysis for each of the variables including minimum, maximum, mean, median, standard deviation, kurtosis, skewness, and confidence level. Along with this analysis, data were studied for completeness. Missing information in the collected data could skew the results and since the sources of data for each variable vary, as discussed above, there was an instance of missing data. Study areas (school districts) with missing data were omitted from the study. The goal was to obtain a complete data set for each variable within each study area to achieve the most reliable results. This data analysis provided an overall description of the data. It was not only essential to obtain a robust dataset, but also a dataset that has a normal distribution.

The General Descriptive tool in PASW created two important types of graphs: histograms and probability plots. These analysis plots offered information on data quality and acted as a precursor for possible data problems in later analysis. The main results to be looked for were outliers and clusters of similar study areas. To create histograms, the range of values in each dataset were broken into continuous bins. The histogram was a visual representation of the number of values that fall within each of those bins. In a normal distribution, the histogram would have showed a bell curve, in which the middle bins would have the greatest number of values, while the lower and higher bins would have the least. The skewness of the histogram described if the normal bell curve favored one side or the other. A histogram skewed to the right would have more values in the bins representing the lower values of the dataset. A histogram could have shown possible outliers which were important to note and understand. Outliers within the plots could have skewed averages largely one way. Also, outliers showed possible study areas that are so unlike the other study areas that certain exclusive features might cause completely different drivers than all other areas.

Similar to a histogram, a probability plot was also used as a visual representation of the distribution of the dataset. In a probability plot one axis represented the values within the given dataset, while the other axis represented the statistic medians or means. The trend line showed the theoretical normal distribution of the data. If the dataset were perfectly distributed all the points would have fallen along the trend line. The degree of variation between the data points and the trend line indicated how closely the dataset distribution was to a normal distribution. If a large difference existed between the data points and the trend line, then it became necessary to check that variable's dataset to understand why this distribution was occurring. A dataset without a normal distribution could have the same or very similar values throughout. Differences between values had to exist to determine if the variable explained any of the dependent variable in the regression analysis.

SECTION 2: CORRELATION ANALYSIS

Using PASW software, a correlation analysis using the Pearson R value was performed in order to test the relationship between all variables within the dataset. The Pearson R correlation value not only expressed the strength of the correlation between variables but also whether that correlation was a negative relationship (as one increases, the other decreases) or a positive relationship (as one increases, the other increases also). Correlation, positive or negative, between independent variables and the dependent variable was important because this was the starting place for predicting which variables might have been important drivers in the regression formula.

High correlation results, negative or positive, between two independent variables showed a possible precursor to multicollinearity issues. Multicollinearity occured when variables that showed a high correlation with one another had a strong relationship and were essentially measuring the same thing. Multicollinearity increased the chances for higher standard error values and wider coefficient confidence intervals. At minimum it was necessary to note and understand any multicollinearity that might have existed within the dataset.

SECTION 3: REGRESSION ANALYSIS

The final analytical step was to perform the regression analysis. The regression method, if chosen and executed correctly, would resulted in a regression formula, which could be used to show the most important variables driving the success of current school based wind power production sites. All regression statistics were performed using the PASW statistical computer program (SPSS, Inc., 2009). I began by using an Enter method regression analysis, in which all independent variables were entered at the same time against the dependent variable. From the

Enter method results, the r-squared value was the most interesting value to consider. The r-squared value essentially told how well the model did at predicting the dependent variable. There were other results equally as important which had to also be examined including the level of significance and the Variance Inflation Factor (VIF) values. The VIF value showed whether multicollinearity was present in the variables. The coefficient results were also very important since these are used in the final regression formula needed for interpretation of the results.

A second regression analysis could be conducted if there were significant problems with the Enter method, such as low r-squared values or high VIF values. For this study, it was logical to run a second regression analysis using the Stepwise method to determine if changes in the r squared value existed in the new model. Also, the Stepwise method allowed the detection of which independent variables would have been significant enough to consider. During the Stepwise method, the program chose the best variables one at a time against the dependent variables and removed variables if the r-squared was increased as a result. The Stepwise method was useful in removing insignificant variables. The same results were considered in this method as in the previous Enter method.

The regression results could be impacted since the locations of the existing Wind for Schools project sites are located sporadically throughout the United States as seen in Figure 1. It might have been possible that based on the data collected some clusters of similar sites would appear, especially within the same areas of the United States. Therefore, using the PASW computer program a cluster analysis was performed to check for clusters. First, a hierarchal cluster analysis was conducted to determine the optimal number of clusters existing within the dataset. The program grouped similar school sites together based on the values in the entire dataset, thus creating a dendrogram diagram. The diagram illustrated which school sites were grouped together in clusters within each step of the analysis. After using the dendrogram diagram to determine the optimal number of clusters, a K-means cluster analysis was ran using the chosen number of clusters. The program determined the optimal clusters configuration and placed each

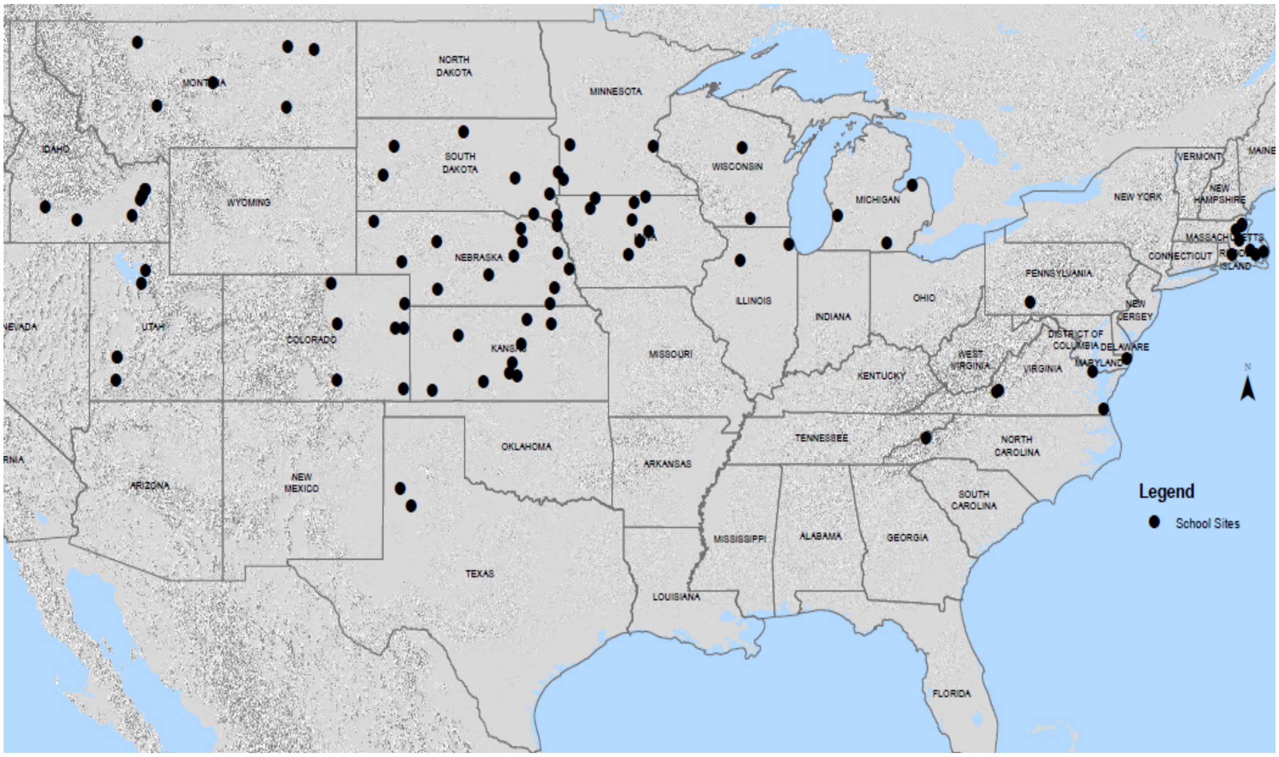

Figure 1. Map of existing Wind for School sites used within this study.

school site into one cluster depending on the number of clusters and the trends within each school site (SPSS, Inc., 2009). Clusters of similar study areas were comparable to outliers in that clusters could also show why certain variables were better drivers for only certain study areas. This was an important consideration during the interpretation of results.

Interpretation of the regression results was required to find the best-fit model or method to use for this data. Once the best analysis method was chosen, the coefficient results were used to determine the most significant drivers for prediction of the dependent variable. Those variables that did not add significantly to the r-squared values were not considered important variables and were eliminated. The variables left were used in the final regression formula.

CHAPTER III

STATISTICAL ANALYSIS RESULTS

In order to find the drivers behind successful installation and usage of the existing school owned wind power production sites within the Wind Powering America Wind Energy for Schools project a three-step analytical analysis, including a General Analysis of the Variables, Correlation Analysis, and Regression Analysis, was executed on the dataset. The dataset consisted of information collected on the dependent variable, Wind Power Generation Capacity, and the following nine dependent variables: Wind Potential, Elevation, Surface Roughness, Rural vs. Urban, District Area Size, School District Population, Number of Students per District, Per Capita Income, and Grants Received. The following three sections detail the statistical results for each of the three steps within the analytical analysis. Section 1 gives on overview of the results of the general analysis of each of the ten variables. The second section, Correlation Analysis Results, details the associations between all of the ten variables analyzing the interactions for relationships or redundancy. Section 3, Regression Analysis Results, explains the outcomes of the multivariate regression analysis and the decisions made based off these results, which ultimately leads to the most complete and reliable list of variables driving the dependent variable. All three sections used the final 90 school sites with complete data for each of the variable.

SECTION 1. RESULTS FROM THE GENERAL ANALYSIS OF THE VARIABLES

For the first step, General Analysis of the Variables, two software programs were used on each of the ten variables to study the variables for trends, completeness, and distribution. The following results from the Excel Data Analysis tool provided the basis for description of trends and completeness: minimum, maximum, mean, median, standard deviation, kurtosis, skewness, and confidence level. The second software program, the SPSS General Descriptive tool output a histogram and probability plot for each of the ten variables and provided a thorough inspection of the distribution of the data.

Wind Power Generation Capacity

The specific descriptive statistic results from the dependent variable wind power generation capacity in Table 5 showed the wind energy capacity of the sites varied from 0.4 kWh at Eagle Rock Jr. High Idaho Falls, Idaho to 1000 kWh at Spirit Lake Community School District in Spirit Lake, Iowa. The average project size of the 90 sites was 2.4 kWh. The histogram of the dependent variable in Figure 2 was right skewed with most of the sites' values being between 0 kWh and 200 kWh. The skewness of this graph showed possible outliers within the dataset, which could cause erroneous results. This was also evident in Figure 3 of the probability plot since the data points did not fall close to the trend line in some areas. Both of these graphs showed outliers which had to stay under consideration as the statistical analysis continued.

Min	**Max**	**Mean**	**Median**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Confidence Level (95.0%)**
0.4	1000	91.37	2.4	228.30	6.91	2.80	45.30

Table 5. Summary of the descriptive statistics of the wind power production capacity.

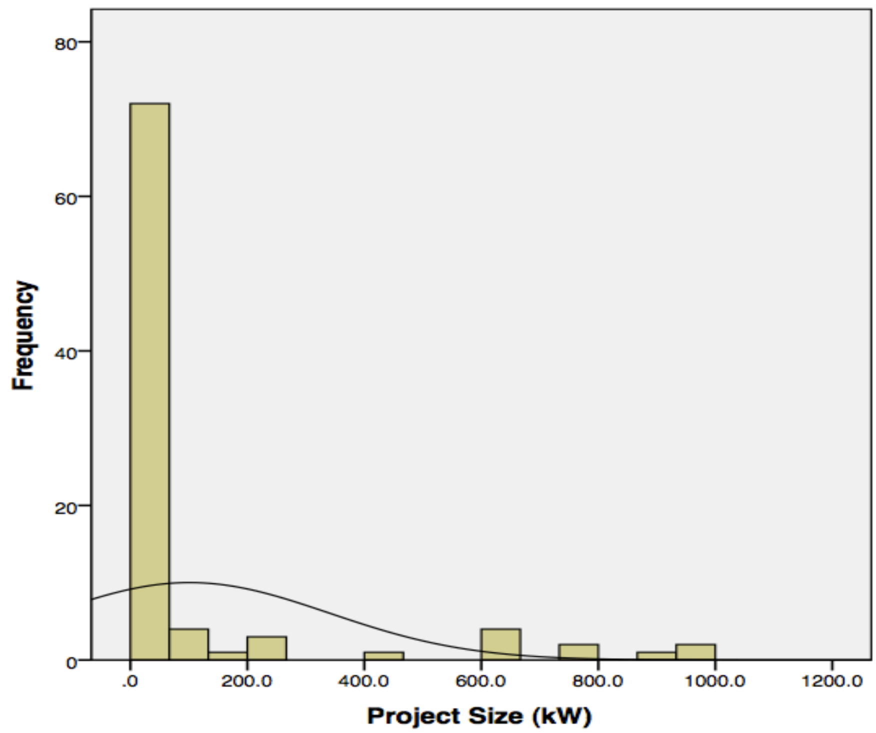

Figure 2. Wind power generation capacity histogram.

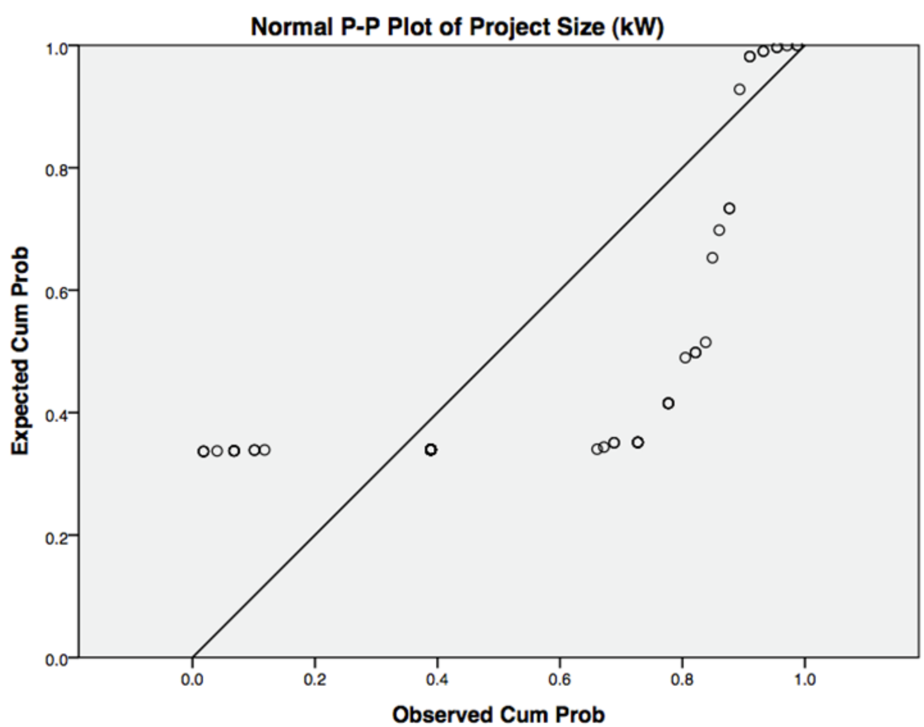

Figure 3. Wind power generation capacity probability plot.

Wind Potential

Even though 7 classes of wind potential exist, the current school sites had wind classes ranging from Class 1 Unsuitable for Development to Class 5 Excellent. The summary of the descriptive statistics found in Table 6 below include the average wind potential class, which indicated the majority of school sites were found to have a wind energy potential class between Class 2 and Class3.

Min	Max	Mean	Median	Standard Deviation	Kurtosis	Skewness	Confidence Level (95.0%)
1	5	2.51	2	0.98	0.12	0.47	0.19

Table 6. Summary of the descriptive statics of the wind potential class variable.

Elevation

The full descriptive statistics summary found in Table 7 below demonstrate out of the 90 school sites 31 had elevations higher than 900 meters (equivalent to 3000 feet) above sea level. These 31 sites' elevations made them susceptible to lower air density and lower wind power production potential. The highest elevation of 1914 meters above sea level was found at John Mall High School in Walsenburg, Colorado while the lowest elevation of three meters above sea level was McGlynn Elementary and Middle School in Medford, Massachusetts. .

Min	Max	Mean	Median	Standard Deviation	Kurtosis	Skewness	Confidence Level (95.0%)
3	1914	652.95	468	503.44	-0.59	0.69	99.89

Table 7. Summary of the descriptive statistics of the elevation above sea level.

The histogram for this variable in Figure 4 was slightly skewed to the left due to the large number of sites with low elevations. In addition to the histogram, the probability plot in Figure 5 also showed good results with the majority of data points falling very close to the trend line. While the data was fairly evenly distributed, the high number of low elevation site caused the small discrepancies seen in the graphs.

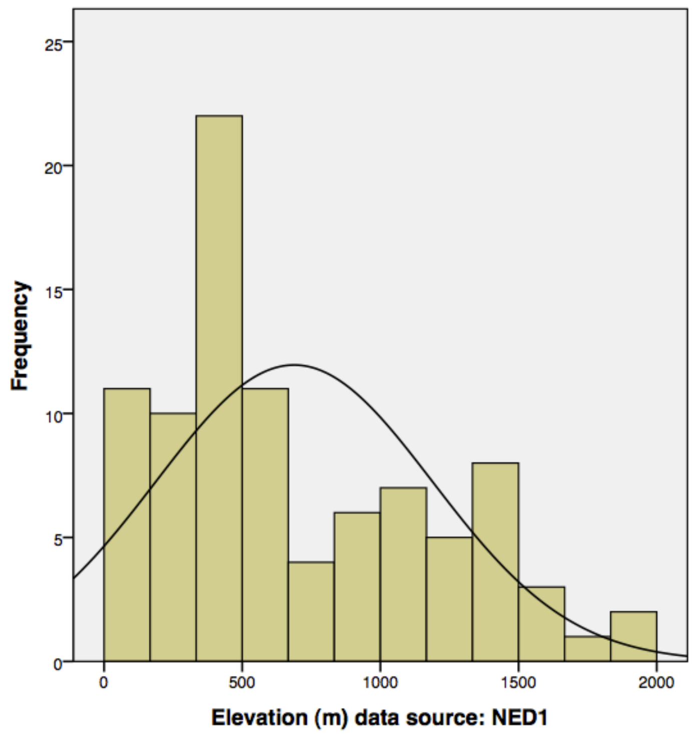

Figure 4. Histogram for the elevation above sea level in meters.

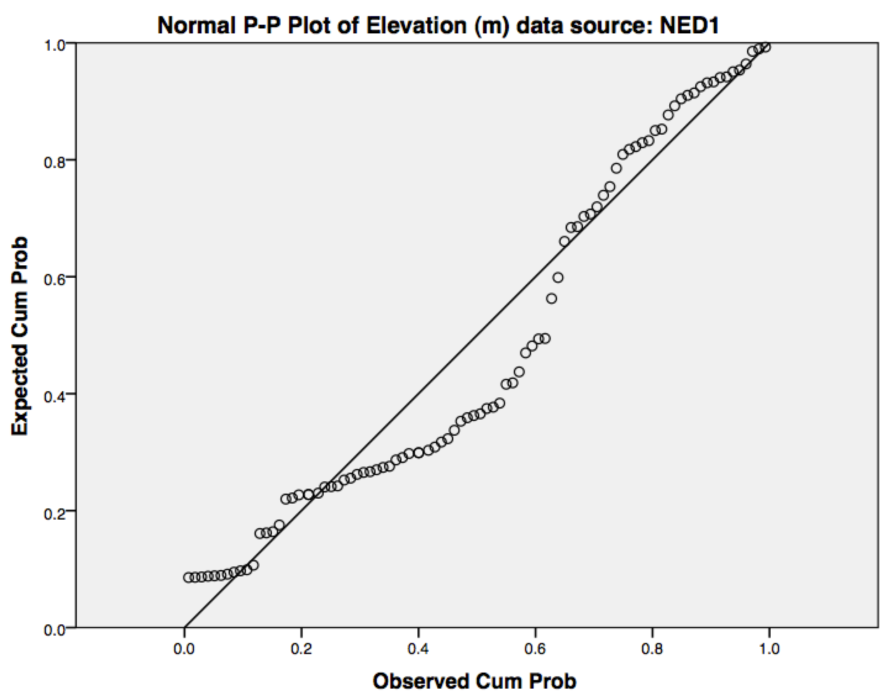

Figure 5. The probability plot for the elevation above sea level.

Surface Roughness

Using Ragheb's "Wind Shear, Roughness Classes and Turbine Energy Production", I created an index for surface roughness which ranked land cover types within the NLCD shapefile as an greater index value as the estimated surface roughness increased (Ragheb, 2011). The surface roughness index values for the school sites' ranged from 1 to 87 with the roughness value of 69 as the most common value. A surface roughness index value of 69 was equivalent to areas with a mixture of man-made surface structures and vegetation. This low intensity residential area's roughness resulted from structures, such as small buildings, accounting for 30-80 percent of the area. The next most common landcover was high intensity residential areas, which has a roughness index value of 82. The roughness values seen in these areas are due to highly developed housing with some large buildings and less than 20 percent vegetation cover.

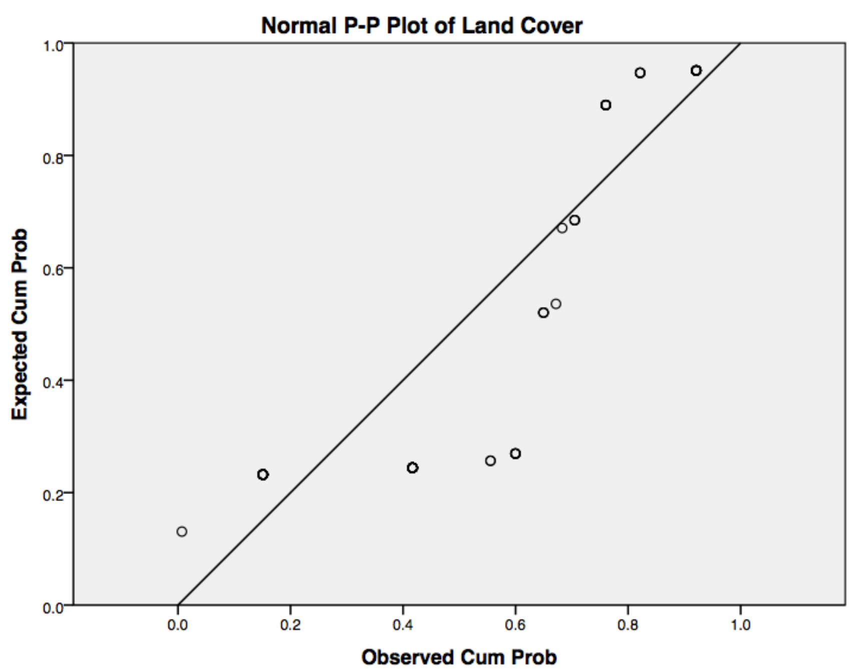

Figure 6. The probability plot of surface roughness estimated from landcover.

The probability plot in Figure 6 shows the data were not perfectly normal. While the data points did follow the general trend line, many plotted far from the line. The skewness seen in this plot was attributed to over half of the school sites located on land tracts with a surface roughness index value of 69 or 87. These two roughness values differ enough that the distribution was not skewed dramatically.

Rural vs. Urban Locations

Rural versus urban location was a binary categorical variable. The histogram shown in Figure 7 was used to compute the number of variables falling within each of the categories. 26 of the 90 school sites were located in areas classified as Urban, meaning the majority of school sites were found in rural areas. Although it was not a requirement that school sites be located in rural settings, the Wind for Schools Project did recognize that fewer urban schools have participated in the program (National Renewable Energy Laboratory 2007).

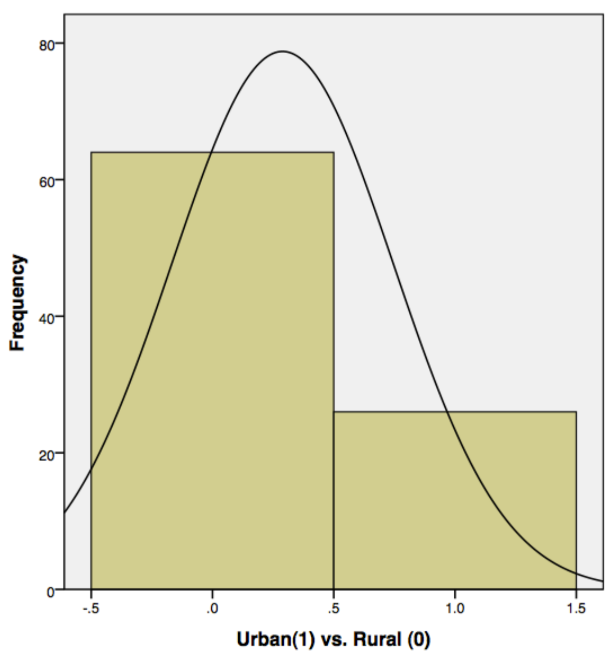

Figure 7. Histogram of urban versus rural school districts.

District Area Size

The district area size variable had the widest range of values of any of the variables used in this study. The smallest sized district was about 1.6 square miles, while the largest school district in land area was about 3296 square miles. The wide range in itself was not a problem, but the histogram in Figure 8 revealed a skewed distribution. 52 of the school sites were located on school districts with 40 to 400 square miles in land area. 27 school sites had district land area size above this range, leaving just 11 schools below this range. The resulting histogram was right skewed with a bell curve that peaked lower than would be expected of a normal distribution. These results proposed a precursor to the possibility of significant outliers, including the smallest and largest district land areas.

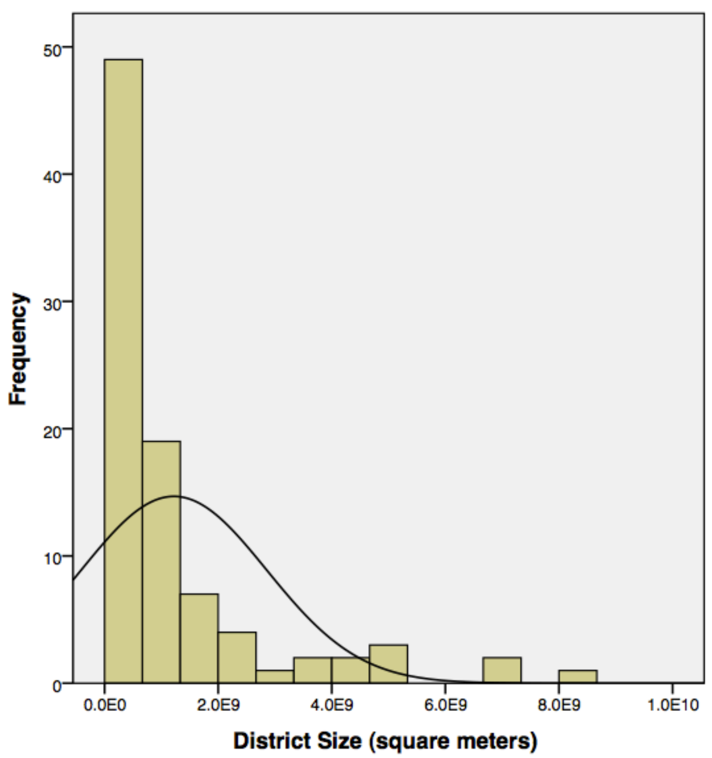

Figure 8. District size histogram in meters squared.

School District Population

Similar to the district area size variable, the school district population also had a wide range of values for the 90 existing school sites. The smallest population of a school district was 661 people, while the largest school district population was 5,257,001 people. The wide range was not the problem with this dataset. As in the previous variable, the problem with this variable was found in the skewed distribution. Figure 9 of the histogram displayed a dramatic right skewed bell curve for the data with 82 of the 90 school sites retaining populations of less than 300,000 people. Eight outliers existed within the dataset, but only one was significant. The second largest school district population was 1,480,260 people, differing from the largest district population by almost 4,000,000 people.

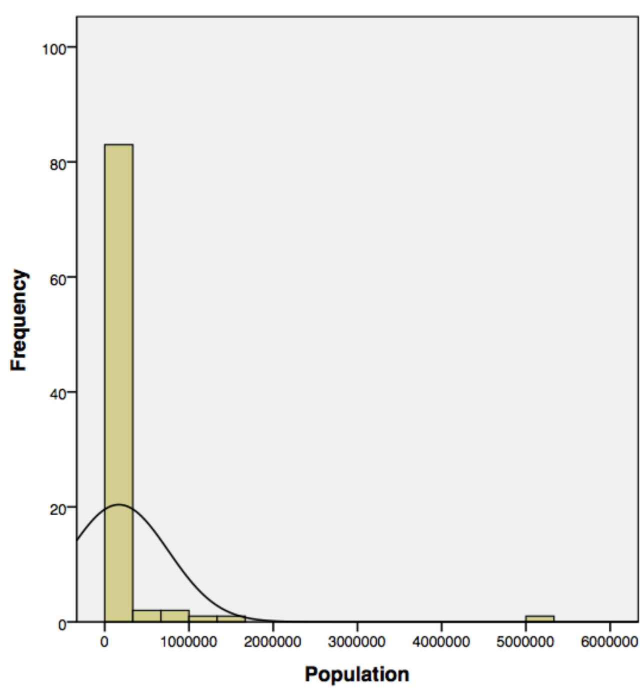

Figure 9. Histogram of the school district population showing significant outlier.

The probability plot in Figure 10 confirmed the striking non-normal distribution by displaying plotted data points almost perfectly perpendicular to the theoretical normal trend line. However, by removing the outlier variables the new histogram and probability plots offered different outcomes with results more closely resembling a normal distribution. Since I was not predicting this variable to be the strongest driver of implementation of school based wind power production, I decided to leave the outliers in the dataset. The outliers' existence were made note of for possible further analysis. If they presented a significant problem, the outliers could be dealt with accordingly.

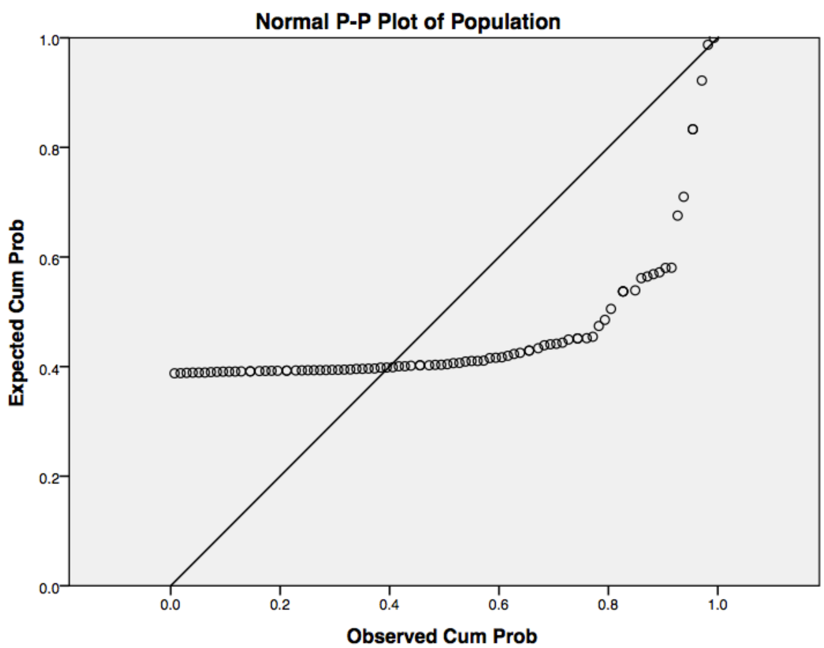

Figure 10. School district population probability plot.

Number of Students per District

While not as extensive as the previous two variables, the number of students per district also had a broad range of values. Valier School district had the least student population with only 57 students in the district, while Virginia Beach Public School district had the most students with a student body of 71,182 pupils. Virginia Beach Public School district was a significant outlier and noticeably affected the data distribution in the histogram in Figure 11. Even though the diagram demonstrated a right skewed distribution, the histogram indicated without the outlier present the data would have shown a far less skewed distribution. Just as in the previous variable, this significant outlier was noted for further investigation if problems arose while computing the other two steps of the statistical analysis.

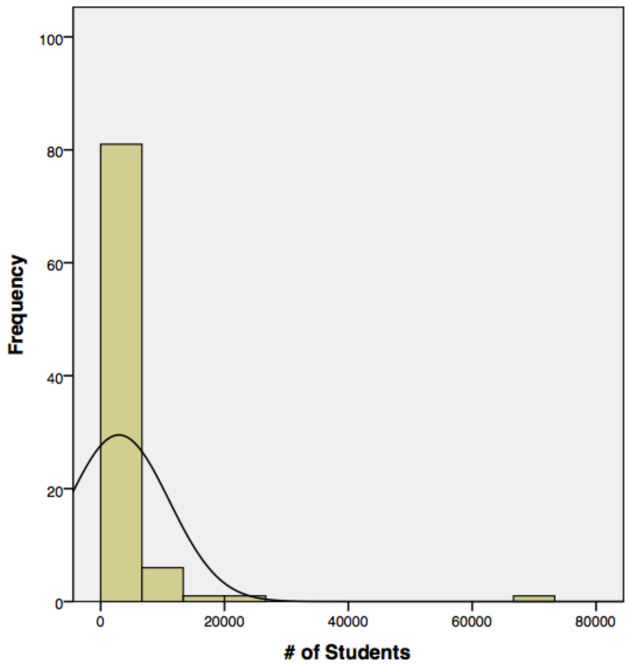

Figure 11. Histogram of the total number of students within the school district.

Per Capita Income

The PCI range of the school site counties differed by about 30,000 dollars from the smallest PCI of 16,263 dollars in Milford School district to the largest PCI of 42,253 dollars in Ponderosa School district. The average PCI of the 90 school districts was 23,857 dollars. This low of an average PCI previewed a potential right skewed distribution. The histogram in Figure 12 showed a slight right skew distribution, but otherwise the PCI of school sites looked fairly evenly distributed. Four minor outliers within the PCI data were responsible for the trivial right skew distribution; however this inconsequential skew was too minor to warrant removing outliers. Figure 13 displayed a probability plot confirming this variable's data was distributed fairly evenly with the data points following along the theoretical normal trend line. Therefore, outliers were noted, but were not removed since they were not expected to significantly alter any results.

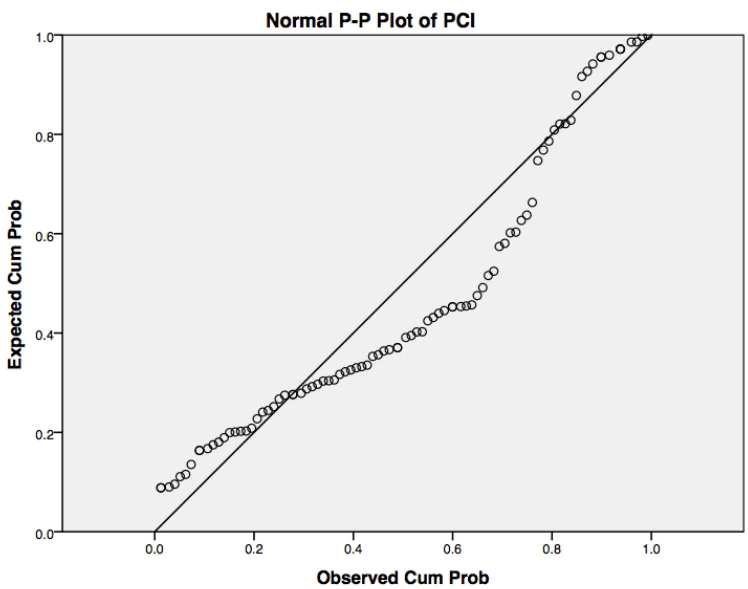

Figure 12. Fairly uniform histogram of the PCI of the school district's county.

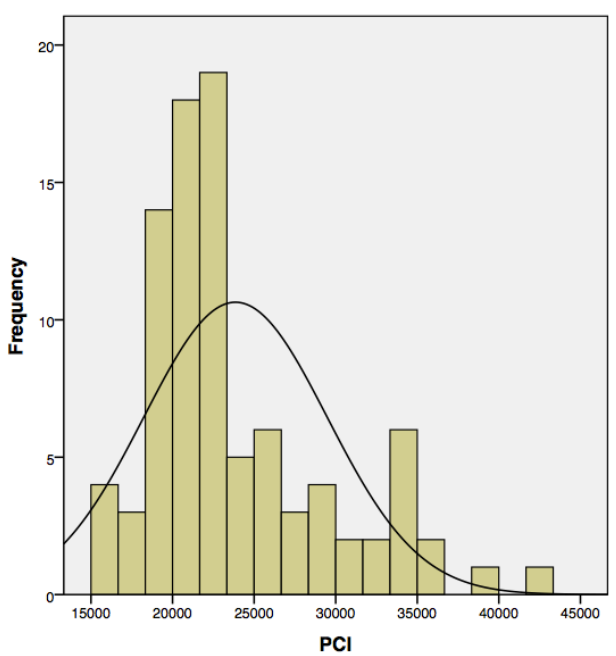

Figure 13. PCI probability plot confirmed a slight skewedness.

Grants Received

The final school site dataset for each of the ten variables was based off the data I was able to acquire for the 90 existing school sites. Three schools, Eagle Rock School in Idaho, Stephen E Decatur School in Maryland, and North Quincy Street School in Maine, all implemented their wind power project without any grant assistance. This was a stark difference from Spirit Lake Community School in Iowa, which received about $120,000 in grant support to install their wind power project. The average amount of grant assistance received by schools was $13,020 per wind power project. This low average grant amount received by schools suggested that Spirit Lake Community School might not have been the only outlier in the data.

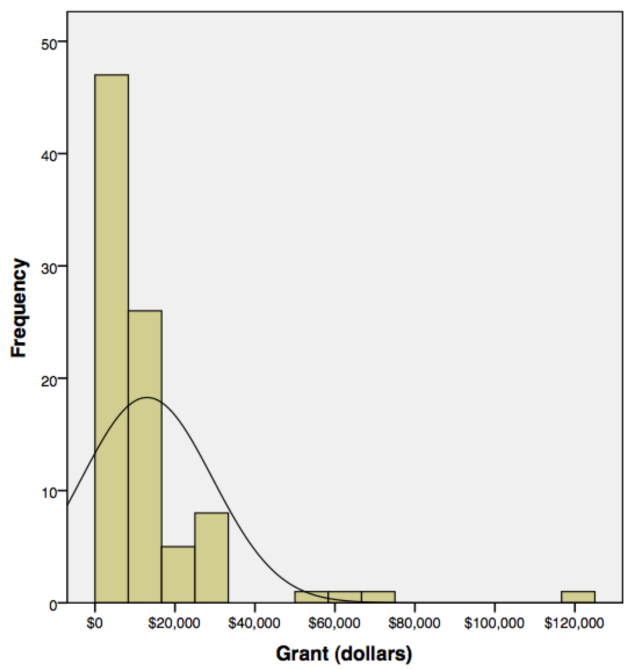

Figure 14. Amount of grant assistantship received histogram.

In Figure 14 the histogram showed a right skewed graph due to four outliers, including the one significant outlier in Spirit Lake Community School. The probability plot shown in Figure 15 displayed a fairly evenly distributed dataset for the amount of dollars received in grants. It was important to note the number of unique values within the data was low at only 19 different values within the 90 school sites. This may have affected the distribution provided in the histogram and probability plots.

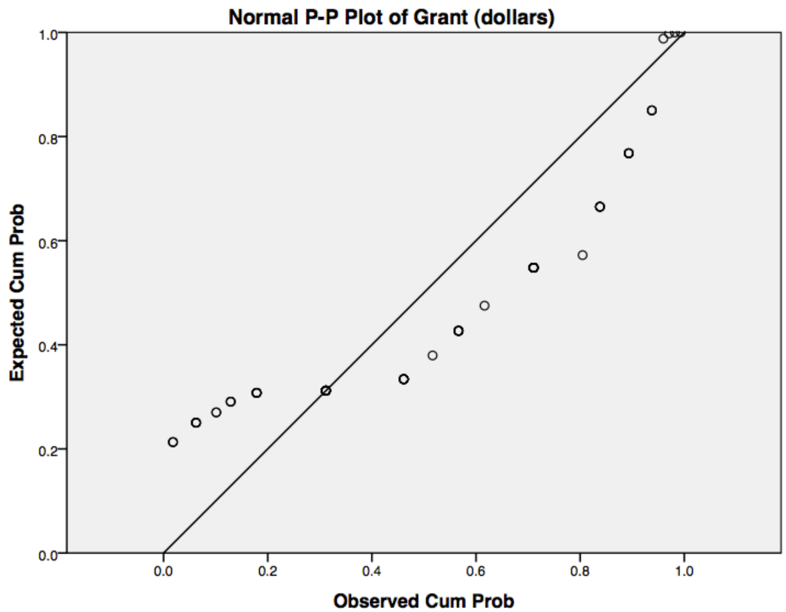

Figure 15. Probability plot for the dollar amount of grants received by each school district.

SECTION 2. CORRELATION RESULTS

The correlation between the ten variables was analyzed using the Pearson R correlation, which presents a possible range -1 to 1 with zero representing no correlation and one (negative or positive) representing perfect correlation. Table 8 was used to first considered correlation values between the dependent variable and the independent variables. Higher values, such as the 0.690 value between project size and the amount of grants received, suggested possible drivers to successful implementation of wind power projects. The only other variables with possible significant correlation with the dependent variable were wind class and elevation, but this correlation was still too low to determine if these would have been considered important drivers of the dependent variable.

The next essential correlation values to consider were correlation between two independent variables, as this could have been a precursor to multicollinearity issues. PCI had significant correlation with elevation and marginal correlation with district area size and district population. The correlation between PCI and elevation was unexpected and difficult to determine the cause behind such an unforeseen relationship. Since the association between these two variables appeared to be random and therefore, the two variables were not measuring the same thing, I ruled out multicollinearity as a concern. The other correlation values were not significant enough to warrant multicollinearity issues. Nonetheless, the VIF values between the variables had to be monitored throughout the regression analysis to make certain no relationship existed between independent variables.

	Project Capacity	**Grants Received**	**# of Students**	**Surface Roughness**	**District Population**	**Elevation**	**District Size**	**Urban vs. Rural**	**PCI**	**Wind Class**
Project Capacity	1	0.69	-0.085	-0.084	-0.083	-0.206	-0.152	-0.089	0.056	0.225
Grants Received		1	0.007	-0.012	-0.041	-0.162	-0.162	-0.065	0.032	0.241
# of Students			1	-0.148	0.068	-0.125	-0.085	-0.017	0.202	-0.135
Surface Roughness				1	-0.119	0.138	0.078	-0.253	-0.032	0.09
District Population					1	-0.176	-0.151	0.264	0.304	-0.201
Elevation						1	0.57	0.125	-0.47	-0.076
District Size							1	0.116	-0.356	-0.118
Urban vs. Rural								1	-0.053	-0.284
PCI									1	-0.217
Wind Class										1

Table 8. Pearson R correlation values for all variables.

SECTION 3. REGRESSION ANALYSIS RESULTS

The final analytical step performed was the regression analysis, which if chosen and executed correctly, would result in a reliable regression formula used to show the most important variables driving the success of the current school based wind power production sites. I began by using an Enter method regression analysis (SPSS, Inc., 2009), in which all independent variables were entered at the same time against the dependent variable. From the enter method results, the r-squared value was calculated as 0.611. This r-squared value was essentially expressing that the model explained 61% of the drivers behind the dependent variable. The Analysis of Variance (ANOVA) table showed the model had a significance level of 0.00, which meant the model could be trusted to explain the dependent variable. The most noteworthy variable in the Enter regression model was the amount of grant assistance received by each school site which had a coefficient value of 0.661. While the high coefficient value was important, it was vital to make sure the significance level was low enough to prove the trustworthiness of the variables. In order to assess the significance of the variables, the t results and the significance results needed to be assessed. For the t values, anything greater than 2 was considered statistically significant. For the significance values, any value less than 0.1 was considered significant. A significance value greater 0.1 meant that there was more than a 10% chance these results were due to chance. The amount of grant assistance received was the only variable with a significance value of less than 0.1 and a t value greater than 2. The amount of grant assistance received was the only variable to be trusted enough to state that it did explain the dependent variable.

Due to the high significance values in eight of the nine independent variables used in the enter method; a second, Stepwise, regression analysis was conducted. The Stepwise method allowed discernment of the statistically significant independent variables. During the Stepwise method, the program chose the best variables one at a time against the dependent variable, and removed any variables if the r-squared was increased as a result. The Stepwise method entered grant assistance received while excluding the other eight variables. This new model produced an

R Square value of 0.576, which was slightly lower than the previous model. However, now the model and all variables used had significance values low enough to be trusted to explain 57.6% of the dependent variable. All VIF values were low enough to exclude multicollinearity as an issue in either model.

Although the final regression model dealt with high significance values and possible correlation between independent variables, there was still a threat of outliers or clusters affecting the results. This was particularly worrisome since the locations of the existing Wind for Schools project sites were located sporadically throughout the United States. It might have been possible that based on the data collected some clusters of similar sites would appear, especially within the same areas of the United States. Therefore, using the PASW computer program a cluster analysis was performed to check for clusters. First, a hierarchal cluster analysis was conducted to determine the optimal number of clusters existing within the dataset. Based on the created dendrogram diagram, it was determined the optimal number of clusters to use was six. The decision on the optimal number of clusters was difficult due to the appearance of three schools as possible outliers for the entire dataset. While the general analysis performed earlier could detail particular schools within each variable as possible outliers, the dendrogram revealed schools which might be outliers for the dataset as a whole, considering all variables together. The three outlier schools were Rhodes School, Virginia Beach City Public Schools, and Spirit Lake Community School District. Since clusters of similar study areas are comparable to outliers, it was determined that a K-means cluster should be performed before any decisions were made over the exclusion of these three schools.

After using the dendrogram diagram to determine the optimal number of clusters, a K-means cluster analysis (SPSS, Inc., 2009) was ran using eight clusters. The program determined the optimal clusters configuration and placed each school site into one cluster depending on the number of clusters and the trends within each school site. Two of the three schools discovered as outliers in the dendogram, Rhodes School and Virginia Beach City Public Schools, were placed in their own two clusters by the K-means cluster analysis. This meant that no other schools were comparable enough to these two sites to be entered into the same cluster. Due to the extremeness of these two outlier schools, I decided to exclude them from the study in anticipation of better regression results. However, the only significant change to the stepwise model was a slightly higher r squared value of 0.579. No other variables were entered or removed within the new model, nor were any significance or VIF values changed between variables. The removal of the two extreme outliers increased the explanation of the model by 0.3%. Based on these results I concluded that while these outliers were dramatically different than other school sites, the difference was not enough to warrant any important change to the model. Therefore, the two outliers were still included in the dataset and further assessed in the interpretation of the results. Clusters of similar study areas were used for further interpretation for trends within certain geographical areas.

CHAPTER IV

STATISTICAL INTERPRETATION

The goal of this study was to produce a list of reliable variables which were the prime drivers behind the implementation of wind power production projects at existing school sites. Through a three-step statistical analysis a final multivariate regression model was chosen resulting in the final regression equation, which is detailed and interpreted in section one of this chapter. The next section combines the interpretation of the variables and regression model with the cluster analysis performed, to see if the geographical location of the school sites plays a part in the drivers of wind power project implementation. The last section in this chapter gives a brief overview of specific Wind Powering America Wind for Schools projects, which offer additional insight into the reliability of the statistical results.

SECTION 1. Regression Model

The final regression method chosen was the Step-wise model. Although this model only used one variable and had a slight lower r-squared value, the Step-wise model produced low enough significance values to be trustworthy in explaining part of the dependent variable. This model removed all insignificant variables and any multicollinearity between variables, while successfully explaining almost 60% of the dependent variable. The regression formulated by this model was as follows:

$$\mathbf{y = -1.715E\text{-}16 + 0.790x}$$

By this equation, it was known that the only one of the possible nine independent variables that had any effect on the dependent variable was the grant assistance received by each school site. This variable is represented in the equation by the symbol x, whereas the dependent variable wind power generation capacity is represented in the equation as the symbol y. As the amount of dollars in grant assistance received by each school increased, so did the wind power generation capacity of each school's project. It seemed worrisome that only one of the possible nine independent variables was statistically important, but this was not completely unexpected.

Schools were chosen as the locations for the wind power projects for several reasons. First, schools offered a built in community for support. In some cases it could be difficult to gain the whole support of a community to install a wind power project (Kildegaard & Myers-Kuykindall, 2006). However, schools offered a large population of stakeholders in the students, teachers, administers, parents, city officials, etc. This large number of stakeholders in support of a project could more easily increase outside knowledge and acceptance of the project. A large backing of stakeholders could also be beneficial when having to negotiate steps in the implementation process such as netting prices, specific zoning locations, additional funding, etc.

Second, by using schools as locations sites this helped to limit implementation to relatively small turbines. The drivers of implementation of community scaled wind projects were different than those of commercial scale. While both community and commercial wind projects focus on funding, the means of funding was different. A commercial wind project entailed more focus on profit, which required that only the most optimal sites were utilized for quicker payback. Siting constraints such as land size, elevation, land cover, and others not focused on in this study such as access to roads and power grids, have proved to be drivers of success for commercial wind projects (American Wind Energy Association, 2012). Commercial scale had to prove that each site was feasible to make a profit and pay back the money that was spent upfront. The regression analysis of this study showed that the amount of grant assistance received was the most significant driver, more important than siting constraints. Community wind projects also needed funding, but by using school districts as location sites the payback period was not as strong of a focus. School's did not necessarily have to first show profitability of the project, only that they could afford the upfront costs and then over time (a longer period than needed in a commercial wind project) make a profit.

As shown, even though the only driver of implementation of wind power projects using school sites was the amount of grant assistance received by each school site, it made a logical strongest driver. Commercial scale wind procure large capital in the planning phase and, to do so, must choose profitable sites with quick payback.. These commercial scale projects had a strong interest in the return on investment (ROI). Community scale wind projects using schools as implementation sites had to first show they had the money to cover the upfront costs of the projects before it could be installed. School sites were less focused on payback periods and ROI, since the schools were a long term investment less focused on pure monetary profit.

SECTION 2. Cases of Wind Project Struggles

I conducted additional investigations into existing school sites and those schools who attempted but were not successful in implementing a wind power project. I found that sources of funding were numerous for school sites. I attempted to capture the most important sources of funding through the variables PCI, number of students per district, school district population, and grant assistance received per school. However, this did not account for all factors affecting the funding of a project. For instance, loans taken out by the school, donations by businesses, etc. all could increase the amount of funding for the wind power project. Additionally, my original study plan included netting price which was essential to funding. The netting price affected how much the school would earn for electricity sold back to the electrical grid. Netting prices were obtained through negotiations with the electricity company, so each site was likely to have a different netting price. This could help increase or decrease funding depending on how negotiations were carried out. Through the following cases it was evident that not only was the size of the installed project driven by funding, but often whether or not to implement the project entirely.

A recent review was conducted over 15 Iowa schools and their attempt, successful or not, to implementing a wind power project. Of the ten successful schools, nine of them were included in my statistical analysis. All of the 15 schools, even the 10 successful projects, emphasized the importance of funding by suggesting that without this the project would not have moved forward. Funding should be the first step taken in the process of implementing a wind power project as seen through the following five schools' struggles. Monson Northwest Webster Community School District received no outside grants and was unable to work out a buyback rate to overcome having to take out such a large loan for the upfront costs of the project. Iowa Falls Community School District planned on funding by loan through a local bank, but the electricity company would not let the district consolidate the meters for net metering. Since an agreement could not be reached which would allow the school to sell back excess electricity, the project had to be cancelled. Iowa City Community School District was able to negotiate a favorable buy back price with the electricity company, but was unable to obtain any grants. Storm Lake Community School District had strong motivations from the community to become more environmentally friendly, however the project was quickly detoured due to low buy back rates quoted from the electrical company. Sioux Central Community School District had a slightly different scenario then the other four Iowa schools, in that they were unable to raise enough support for a wind power project due to the high costs and low buy back rate quoted by the electrical company (Galluzzo, T. & Osterberg, D. 2006).

Iowa schools were not the only area were funding has proved to be a major hurdle not all have managed. In 2010, thirteen Alaska schools applied to be part of the Wind Powering America Wind for Schools project, but over half of these schools were unable to acquire enough funding for implementation. Each of the Colorado school sites in this study were able to continue with installation with the aid of three or more grants per site. Ponderosa High School in Flagstaff, Arizona was only able to install a wind power project thanks to five local businesses' donations in addition to the state level grant received. In fact, most schools were only able to afford the high upfront costs of a wind power project through multiples sources of income, including grants, outside donations, and loans (Baranowski, R. 2012).

SECTION 3. Cluster Analysis

Clusters of school sites with similar data in the previously chosen variables were evaluated for trends within certain geographical areas. Since the two extreme outliers, Virginia Beach City Public Schools and Rhodes School, were kept within the dataset, they each encompass a cluster group to themselves (Cluster 2 and Cluster 4). Cluster 6 was only comprised of two schools, Spirit Lake community School District and Pipestone Area School District. These two schools received the highest amount of grants of all school sites, \$120,000 and \$70,000 respectively. This left 86 school sites in three clusters for a geographical assessment.

All sites were colored based on their assigned clusters through the K-means cluster analysis (SPSS, Inc. 2009) and mapped in Figure 16 to determine if spatial trends between clusters existed. Cluster 1 showed the most prominent spatial trend with all school sites within this cluster found in central United States. This cluster consisted of school sites found in the following states: Colorado, Iowa, Kansas, Southern Nebraska, South Dakota, and Texas. Cluster 5 also showed a strong spatial trend with all school sites within this cluster found in western United States. This cluster consisted of all school sites found in Montana, Utah, and all but two school sites in Idaho. Additionally, two of the school sites in Colorado were also placed in this cluster. Finally, Cluster 3 school sites were found mostly in eastern United States with a few sites found in central United States in Nebraska and western United States in Idaho.

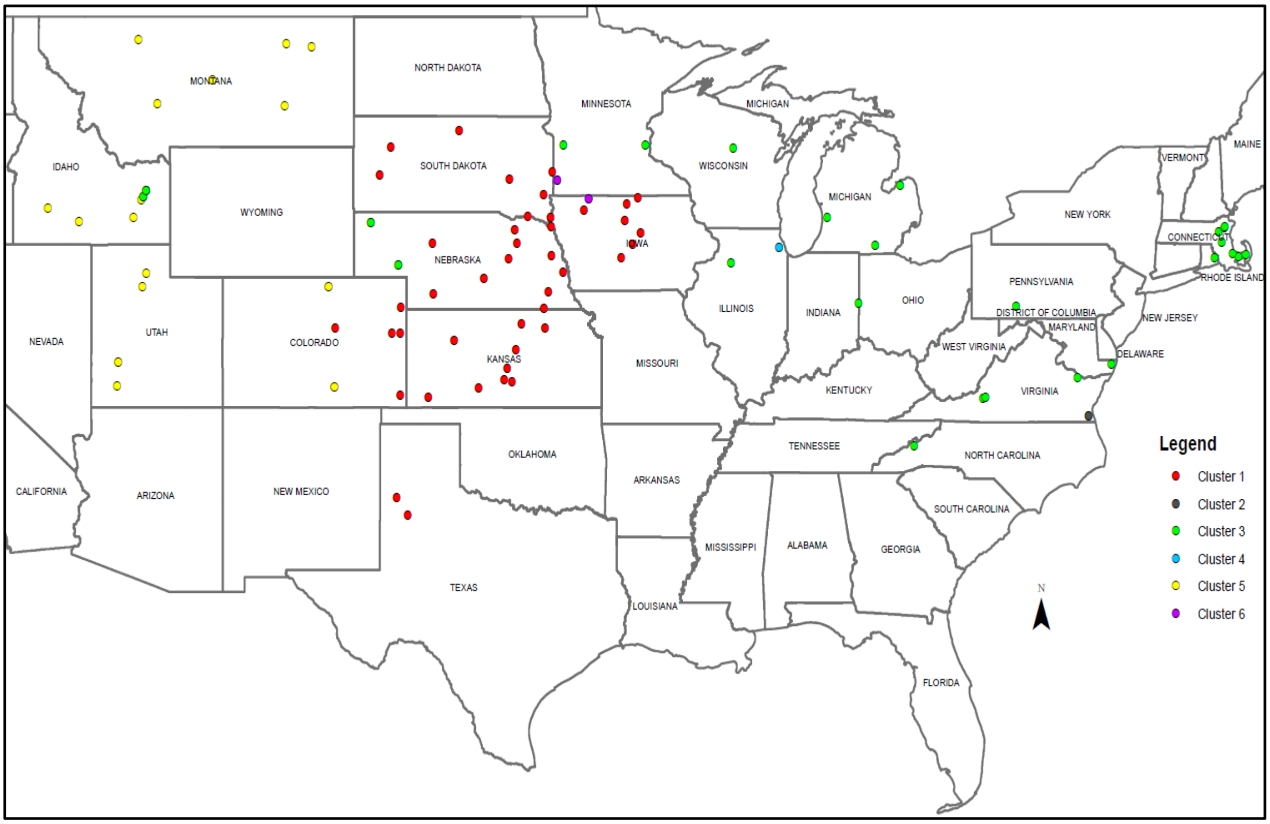

Figure 16. Cluster map interpretation on spatial trends in school sites (National Renewable Energy Laboratory, 2012).

The cluster analysis provided the essential conclusion that the geographical area of the United States in which the school wind power project was located may have played a role in implementation, which was not taken into consideration in the possible drivers of the regression analysis. Some of the variables used in the regression formula are driven by geographical location such as wind class, land cover, and elevation. However, since none of these variables proved to be a significant driver in the regression analysis, the spatial trend might not have been adequately incorporated.

CHAPTER V

OKLAHOMA'S COMMUNITY WIND

In addition to illustrating evidence of geographical trends within school sites in the Wind for Schools program, the cluster analysis also provided valuable information for Oklahoma to use while contemplating whether to take part in using school sites for implementation locations for wind power projects. In order to use this information, first the wind power available and currently being used in Oklahoma must be considered. Second, the interest in wind power already existing in the state must be made aware of. Lastly, combine this background knowledge with an in depth look into the sites within Cluster 1 of the cluster analysis.

Oklahoma was not included in the Wind for Schools program due to a lack of wind. Oklahoma ranked 9th in the country for wind power potential and recently moved to 4th in the nation for installed wind power capacity. The 3,134 megawatts of installed wind power capacity in 2012 from the commercial scale projects across the state accounted for 10.5% of the total electrical generation in Oklahoma (American Wind Energy Association, 2013). The best resources in state could be found in the panhandle and western Oklahoma as seen in Figure 17 below. Certain areas in western Oklahoma had wind speeds over eight meters per second, which made it an outstanding location for wind development (National Renewable Energy Laboratory , 2012).

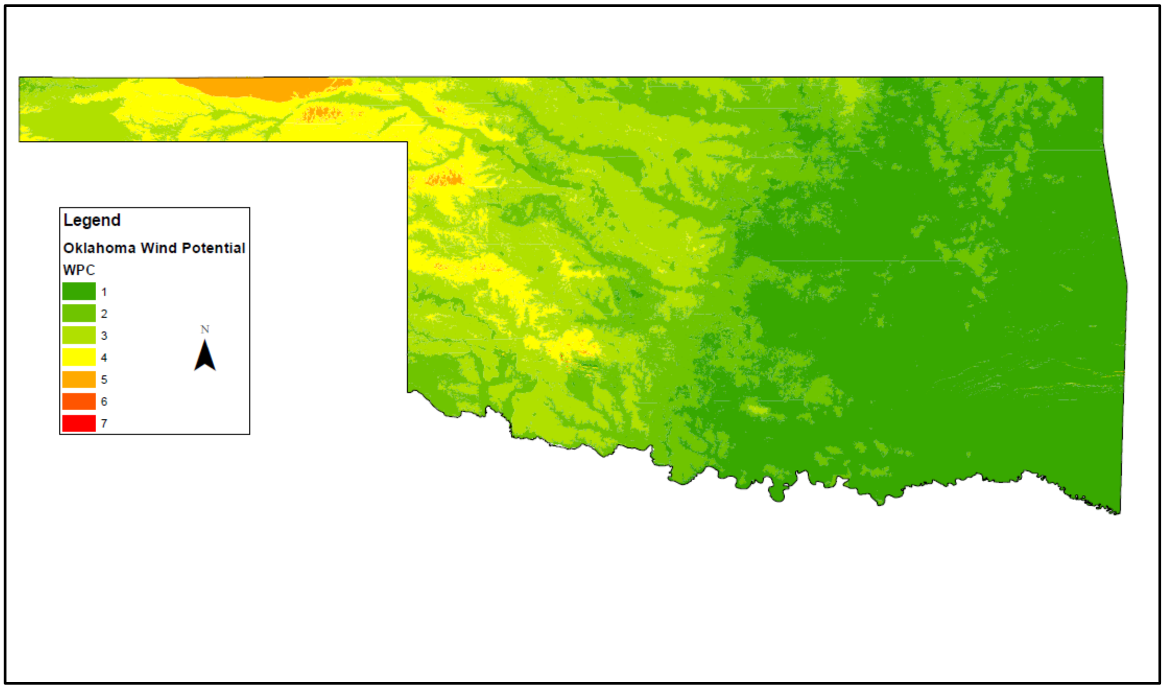

Figure 17. Classified wind power potential in Oklahoma.

In addition to the high potential wind resource available in Oklahoma, a large group of wind power development advocates exist within the state. These advocates can be found in several groups including the Oklahoma Renewable Energy Council, Oklahoma Department of Commerce, and the Oklahoma Wind Power Initiative. Interactive maps and hand books are just a few of the resources provided by these advocate groups (Oklahoma Wind Power Initiative, 2010). Local universities across the state have also partnered with the groups supplying experts and information. Partnerships are not the only way local universities are supporting wind power. They are also offering educational courses for wind power careers and installing their own wind power farms (University of Oklahoma, 2012).

With all the interest and wind resource available, some advocates have attempted to bring community scaled wind projects to the state in the past (Stadler, 2012). These attempts failed for various reasons, but funding has been an issue. The rich background of interest and resources could have offered the support needed for a project like this without participating in the Wind for

Schools program. Since previous project proposals failed, it was essential to look back at the cluster analysis results. Cluster 1 was important not only due to its high spatial trend, but also because the spatial area of this cluster encompassed the same geographical area as Oklahoma (Figure 18). This cluster consisted of school sites found in the following states: Colorado, Iowa, Kansas, Southern Nebraska, South Dakota, and Texas.

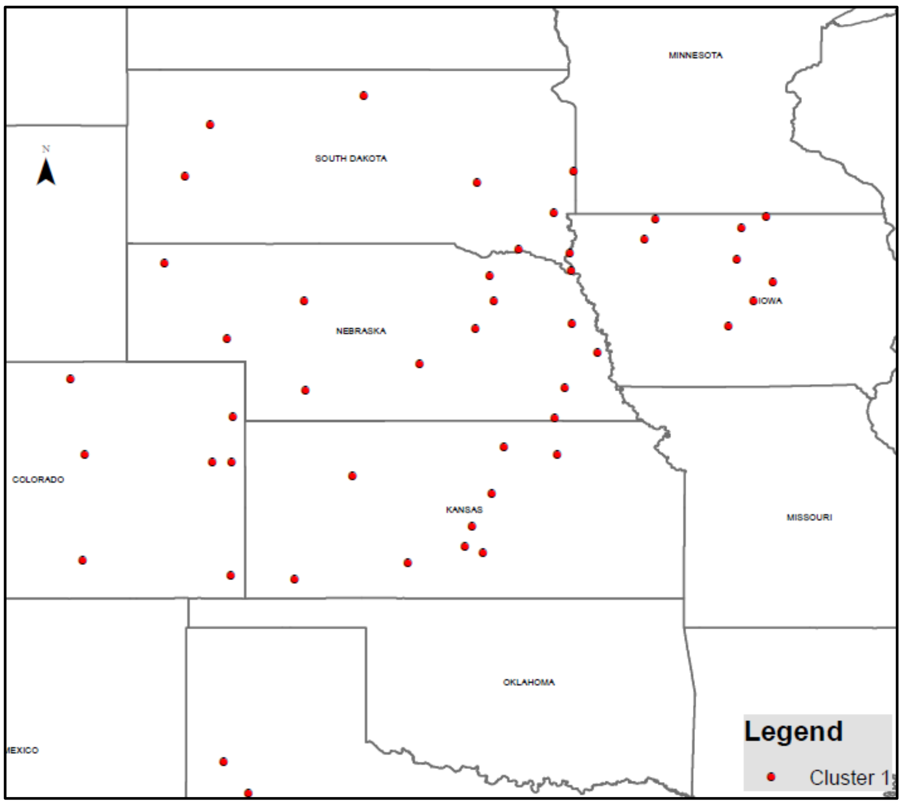

Figure 18. Location of school sites within Cluster 1.

As seen in Table 9, the cluster had relative large wind power generation capacity, large grant assistance received, low district population, were in rural areas, and, most notably, were in favorable wind classes. The average wind class found in the school sites within Cluster 1 was 3 or higher. Most of the sites also had district populations under 60,000. Interestingly, the elevation of the school sites within Cluster 1 almost all feel between 400 and 700 meters above sea level. If school sites in Oklahoma received funding support to overcome the high installation cost of the project, the ideal locations could be those school districts located in high wind potential areas, such as western Oklahoma, and low populated rural areas.

City	County	State	Project Size (kW)	Grant (dollars)	Wind Class	Population	Urban(1) vs. Rural (0)
Walsh	Baca	CO	2.4	5000	4	3847	0
Burlington	Kit Carson	CO	2.4	5000	3	8072	0
Stratton	Kit Carson	CO	2.4	5000	3	8072	0
Wray	Yuma	CO	900	25000	3	9630	0
Royal	Clay	IA	95	10000	4	16676	0
Eldora	Hardin	IA	750	30000	3	17486	0
Akron	Plymouth	IA	600	25000	3	24356	1
Nevada	Story	IA	450	15000	3	84780	0
Forest City	Winnebago	IA	600	25000	3	10835	1
Northwood	Worth	IA	250	15000	3	7620	0
Clarion	Wright	IA	50	10000	3	13039	0
Concordia	Cloud	KS	2.4	5000	3	9367	1
Quinter	Gove	KS	50	15000	4	2599	0
Greensburg	Kiowa	KS	50	15000	4	2646	1
Langdon	Reno	KS	2.4	5000	3	63214	0
Pretty Prairie	Reno	KS	2.4	5000	3	63214	0
Randolph	Riley	KS	2.4	5000	2	69706	0
Brookville	Saline	KS	2.4	5000	3	54076	0
Moscow	Stevens	KS	50	15000	5	5145	0
Pleasanton	Buffalo	NE	2.4	16000	2	44877	0
Hooper	Dodge	NE	2.4	15000	3	35774	0
Odell	Gage	NE	2.4	15000	3	22935	0
Hayes Center	Hayes	NE	2.4	15000	3	1044	0
Mullen	Hooker	NE	1.8	5000	3	661	0
Creighton	Knox	NE	2.4	15000	3	8566	0
Firth	Lancaster	NE	2.4	15000	3	274432	0
Elkton	Brookings	SD	2.4	3000	4	29437	0
Faith	Meade	SD	2.4	6000	5	24126	0
Sioux Falls	Minnehaha	SD	2.4	10000	4	175749	0
Box Elder	Pennington	SD	2.4	6000	5	96903	0
Forestburg	Sanborn	SD	2.4	8000	3	2458	0
Selby	Walworth	SD	2.4	6000	4	5312	0
Yankton	Yankton	SD	2.4	5000	3	21771	0
Earth	Lamb	TX	100	25000	3	13741	1
Shallowater	Lubbock	TX	250	50000	3	262985	1

Table 9. School sites placed in the cluster encompassing Oklahoma.

CHAPTER VI

CONCLUSION

Implementation of a community wind project is complicated and riddled with hurdles, as seen throughout the numerous examples given previously. The purpose of this study is to identify the drivers behind successful production of current wind power installed in schools. Through an analytical analysis of the most prominent drivers of community wind development, it is seen that the largest roadblock faced by the community wind development within school districts is a source of funding. This driver alone accounts for about 60% of the explanation of wind power installation capacity as shown through the regression model preformed on the existing schools within the Wind for School Project.

The Wind for Schools Project is continuing to grow and more schools across the nation are participating in the program or similar programs. As the program matures more data and experience from these schools are available to be studied and learned from. As a result it is possible that as more data becomes available, the present study could be updated and more specific information could result. Material added includes additional data to add net metering or other possible drivers not included in this original study. Also, as schools begin reporting actual energy produced from the wind power projects this could result in a more efficient dependent variable than the wind project power capacity used in this study. All of these areas of growth and improvement over time will lead to supplementary information and a need for a re-investigation to determine the remaining 40% of the explanation of the drivers for wind power implementation not determined in this study. Increased reliability of a study of this kind will provide an escalation in community support of wind power projects.

Additional studies could also be performed focusing on those schools in cluster one of this study to directly relate to how Oklahoma might perform. This cluster is important because the spatial area of this cluster encompass Colorado, Iowa, Kansas, Southern Nebraska, South Dakota, and Texas, the same geographical area as Oklahoma. By solely focusing on the high level similarities seen in this study between the school sites within this cluster, such as large wind power generation capacity, large grant assistance received, high wind class, low district population, rural areas, and most notably high wind class, the beginnings of what Oklahoma should focus on for implementation is already given. Supplementary studies into these specific schools might give improved insight into the plausibility of success for Oklahoma to implement wind power. This could give further proof and ultimately lead to greatly needed additional community support within the state for wind power projects.

There are significant benefits to community wind power that cannot be disregarded. Social, economic, and environmental benefits exist to the entire community in which a community-scaled wind power project is implemented. The regression analysis suggests that if the funding sources can be reached, these benefits far outweigh the struggles of implementation. Many school projects only transpired due to funding received from external donations within the community. Therefore one can extrapolate the importance of community support for these projects. Community backing for a school based wind power project can come in several forms including donations, increased pressure on electrical companies for better buy back rates, increased pressure for grants, morale support, etc. No matter the form community support takes on, it is detrimental to the success of any community wind power project. While schools offer a unique built-in support system, this is only a starting block. Community wind power projects of all sizes and located in all places need the community's support and in a world with rapid increasing energy usage trends, the community likewise requires the support of wind power projects. Once realized, this mutually needed relationship could provide a brighter future for all.

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